```
Name : Tupakula Vaishnavi
In [2]: ▶
           import numpy as np
            import pandas as pd
            import matplotlib.pyplot as plt
            import seaborn as sns
In [3]:
         Out[3]: ['anagrams',
             'anscombe',
             'attention',
             'brain networks',
             'car_crashes',
             'diamonds',
             'dots',
             'dowjones',
             'exercise',
             'flights',
             'fmri',
             'geyser',
             'glue',
             'healthexp',
             'iris',
             'mpg',
             'penguins',
             'planets',
             'seaice',
             'taxis',
             'tips',
             'titanic']
In [4]:
         ▶ | df=sns.load_dataset('car_crashes')
```

In [5]: ▶ df

Out[5]:

	total	speeding	alcohol	not_distracted	no_previous	ins_premium	ins_losses	abbrev
0	18.8	7.332	5.640	18.048	15.040	784.55	145.08	AL
1	18.1	7.421	4.525	16.290	17.014	1053.48	133.93	AK
2	18.6	6.510	5.208	15.624	17.856	899.47	110.35	AZ
3	22.4	4.032	5.824	21.056	21.280	827.34	142.39	AR
4	12.0	4.200	3.360	10.920	10.680	878.41	165.63	CA
5	13.6	5.032	3.808	10.744	12.920	835.50	139.91	СО
6	10.8	4.968	3.888	9.396	8.856	1068.73	167.02	СТ
7	16.2	6.156	4.860	14.094	16.038	1137.87	151.48	DE
8	5.9	2.006	1.593	5.900	5.900	1273.89	136.05	DC
9	17.9	3.759	5.191	16.468	16.826	1160.13	144.18	FL
10	15.6	2.964	3.900	14.820	14.508	913.15	142.80	GA
11	17.5	9.450	7.175	14.350	15.225	861.18	120.92	HI
12	15.3	5.508	4.437	13.005	14.994	641.96	82.75	ID
13	12.8	4.608	4.352	12.032	12.288	803.11	139.15	IL
14	14.5	3.625	4.205	13.775	13.775	710.46	108.92	IN
15	15.7	2.669	3.925	15.229	13.659	649.06	114.47	IA
16	17.8	4.806	4.272	13.706	15.130	780.45	133.80	KS
17	21.4	4.066	4.922	16.692	16.264	872.51	137.13	KY
18	20.5	7.175	6.765	14.965	20.090	1281.55	194.78	LA
19	15.1	5.738	4.530	13.137	12.684	661.88	96.57	ME
20	12.5	4.250	4.000	8.875	12.375	1048.78	192.70	MD
21	8.2	1.886	2.870	7.134	6.560	1011.14	135.63	MA
22	14.1	3.384	3.948	13.395	10.857	1110.61	152.26	MI
23	9.6	2.208	2.784	8.448	8.448	777.18	133.35	MN
24	17.6	2.640	5.456	1.760	17.600	896.07	155.77	MS
25	16.1	6.923	5.474	14.812	13.524	790.32	144.45	МО
26	21.4	8.346	9.416	17.976	18.190	816.21	85.15	MT
27	14.9	1.937	5.215	13.857	13.410	732.28	114.82	NE
28	14.7	5.439	4.704	13.965	14.553	1029.87	138.71	NV
29	11.6	4.060	3.480	10.092	9.628	746.54	120.21	NH
30	11.2	1.792	3.136	9.632	8.736	1301.52	159.85	NJ
31	18.4	3.496	4.968	12.328	18.032	869.85	120.75	NM
32	12.3	3.936	3.567	10.824	9.840	1234.31	150.01	NY
33	16.8	6.552	5.208	15.792	13.608	708.24	127.82	NC
34	23.9	5.497	10.038	23.661	20.554	688.75	109.72	ND

	total	speeding	alcohol	not_distracted	no_previous	ins_premium	ins_losses	abbrev
35	14.1	3.948	4.794	13.959	11.562	697.73	133.52	ОН
36	19.9	6.368	5.771	18.308	18.706	881.51	178.86	OK
37	12.8	4.224	3.328	8.576	11.520	804.71	104.61	OR
38	18.2	9.100	5.642	17.472	16.016	905.99	153.86	PA
39	11.1	3.774	4.218	10.212	8.769	1148.99	148.58	RI
40	23.9	9.082	9.799	22.944	19.359	858.97	116.29	sc
41	19.4	6.014	6.402	19.012	16.684	669.31	96.87	SD
42	19.5	4.095	5.655	15.990	15.795	767.91	155.57	TN
43	19.4	7.760	7.372	17.654	16.878	1004.75	156.83	TX
44	11.3	4.859	1.808	9.944	10.848	809.38	109.48	UT
45	13.6	4.080	4.080	13.056	12.920	716.20	109.61	VT
46	12.7	2.413	3.429	11.049	11.176	768.95	153.72	VA
47	10.6	4.452	3.498	8.692	9.116	890.03	111.62	WA
48	23.8	8.092	6.664	23.086	20.706	992.61	152.56	WV
49	13.8	4.968	4.554	5.382	11.592	670.31	106.62	WI
50	17.4	7.308	5.568	14.094	15.660	791.14	122.04	WY

In [6]: ► df.info

Out[6]:	<bou< th=""><th></th><th></th><th>me.info of s_premium \</th><th>total spee</th><th>ding alcohol</th><th>not_distra</th></bou<>			me.info of s_premium \	total spee	ding alcohol	not_distra
	0	18.8	7.332	5.640	18.048	15.040	784.55
		18.1	7.332		16.290	17.014	1053.48
	1			4.525			899.47
	2	18.6	6.510	5.208	15.624	17.856	
	3	22.4	4.032	5.824	21.056	21.280	827.34
	4	12.0	4.200	3.360	10.920	10.680	878.41
	5	13.6	5.032	3.808	10.744	12.920	835.50
	6	10.8	4.968	3.888	9.396	8.856	1068.73
	7	16.2	6.156	4.860	14.094	16.038	1137.87
	8	5.9	2.006	1.593	5.900	5.900	1273.89
	9	17.9	3.759	5.191	16.468	16.826	1160.13
	10	15.6	2.964	3.900	14.820	14.508	913.15
	11	17.5	9.450	7.175	14.350	15.225	861.18
	12	15.3	5.508	4.437	13.005	14.994	641.96
	13	12.8	4.608	4.352	12.032	12.288	803.11
	14	14.5	3.625	4.205	13.775	13.775	710.46
	1 5	15.7	2.669	3.925	15.229	13.659	649.06
	16	17.8	4.806	4.272	13.706	15.130	780.45
	17	21.4	4.066	4.922	16.692	16.264	872.51
	18	20.5	7.175	6.765	14.965	20.090	1281.55
	19	15.1	5.738	4.530	13.137	12.684	661.88
	20	12.5	4.250	4.000	8.875	12.375	1048.78
	21	8.2	1.886	2.870	7.134	6.560	1011.14
	22	14.1	3.384	3.948	13.395	10.857	1110.61
	23	9.6	2.208	2.784	8.448	8.448	777.18
	24	17.6	2.640	5.456	1.760	17.600	896.07
	25	16.1	6.923	5.474	14.812	13.524	790.32
	26	21.4	8.346	9.416	17.976	18.190	816.21
	27	14.9	1.937	5.215	13.857	13.410	732.28
	28	14.7	5.439	4.704	13.965	14.553	1029.87
	29	11.6	4.060	3.480	10.092	9.628	746.54
	30	11.2	1.792	3.136	9.632	8.736	1301.52
	31						
		18.4	3.496	4.968	12.328	18.032	869.85
	32	12.3	3.936	3.567	10.824	9.840	1234.31
	33	16.8	6.552	5.208	15.792	13.608	708.24
	34	23.9	5.497	10.038	23.661	20.554	688.75
	35	14.1	3.948	4.794	13.959	11.562	697.73
	36	19.9	6.368	5.771	18.308	18.706	881.51
	37	12.8	4.224	3.328	8.576	11.520	804.71
	38	18.2	9.100	5.642	17.472	16.016	905.99
	39	11.1	3.774	4.218	10.212	8.769	1148.99
	40	23.9	9.082	9.799	22.944	19.359	858.97
	41	19.4	6.014	6.402	19.012	16.684	669.31
	42	19.5	4.095	5.655	15.990	15.795	767.91
	43	19.4	7.760	7.372	17.654	16.878	1004.75
	44	11.3	4.859	1.808	9.944	10.848	809.38
	45	13.6	4.080	4.080	13.056	12.920	716.20
	46	12.7	2.413	3.429	11.049	11.176	768.95
	47	10.6	4.452	3.498	8.692	9.116	890.03
	48	23.8	8.092	6.664	23.086	20.706	992.61
	49	13.8	4.968	4.554	5.382	11.592	670.31
	50	17.4	7.308	5.568	14.094	15.660	791.14
		-					 -

ins_losses abbrev 0 145.08 AL 1 133.93 AK

2	110.35	ΑZ
3	142.39	AR
4	165.63	CA
5	139.91	CO
6	167.02	CT
7	151.48	DE
8	136.05	DC
9	144.18	FL
10	142.80	GA
11	120.92	HI
12	82.75	ID
13	139.15	IL
 14	108.92	IN
15	114.47	IA
16	133.80	KS
17	137.13	KY
18	194.78	LA
19	96.57	ME
20	192.70	MD
21	135.63	MA
22	152.26	MI
22 23	133.35	MN
2 <i>3</i> 24	155.77	MS
24 25		
	144.45 85.15	MO
26		MT
27	114.82	NE
28	138.71	NV
29	120.21	NH
30	159.85	NJ
31	120.75	NM
32	150.01	NY
33	127.82	NC
34	109.72	ND
35	133.52	ОН
36	178.86	OK
37	104.61	OR
38	153.86	PA
39	148.58	RI
40	116.29	SC
41	96.87	SD
42	155.57	TN
43	156.83	TX
44	109.48	UT
45	109.61	VT
46	153.72	VA
47	111.62	WA
48	152.56	WV
49	106.62	WI
50	122.04	WY

In [7]: ► df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 51 entries, 0 to 50
Data columns (total 8 columns):

#	Column	Non-Null Count	Dtype
0	total	51 non-null	float64
1	speeding	51 non-null	float64
2	alcohol	51 non-null	float64
3	<pre>not_distracted</pre>	51 non-null	float64
4	no_previous	51 non-null	float64
5	ins_premium	51 non-null	float64
6	ins_losses	51 non-null	float64
7	abbrev	51 non-null	object
	63	1 1 1 / 4 3	

dtypes: float64(7), object(1)

memory usage: 3.3+ KB

In [8]: ▶ df.describe()

Out[8]:

	total	speeding	alcohol	not_distracted	no_previous	ins_premium	ins_los
count	51.000000	51.000000	51.000000	51.000000	51.000000	51.000000	51.000
mean	15.790196	4.998196	4.886784	13.573176	14.004882	886.957647	134.493
std	4.122002	2.017747	1.729133	4.508977	3.764672	178.296285	24.835
min	5.900000	1.792000	1.593000	1.760000	5.900000	641.960000	82.750
25%	12.750000	3.766500	3.894000	10.478000	11.348000	768.430000	114.645
50%	15.600000	4.608000	4.554000	13.857000	13.775000	858.970000	136.050
75%	18.500000	6.439000	5.604000	16.140000	16.755000	1007.945000	151.870
max	23.900000	9.450000	10.038000	23.661000	21.280000	1301.520000	194.780
4							•

In [9]: ► df.head()

Out[9]:

	total	speeding	alcohol	not_distracted	no_previous	ins_premium	ins_losses	abbrev
0	18.8	7.332	5.640	18.048	15.040	784.55	145.08	AL
1	18.1	7.421	4.525	16.290	17.014	1053.48	133.93	AK
2	18.6	6.510	5.208	15.624	17.856	899.47	110.35	AZ
3	22.4	4.032	5.824	21.056	21.280	827.34	142.39	AR
4	12.0	4.200	3.360	10.920	10.680	878.41	165.63	CA

In [10]: ► df.tail()

Out[10]:

	total	speeding	alcohol	not_distracted	no_previous	ins_premium	ins_losses	abbrev
46	12.7	2.413	3.429	11.049	11.176	768.95	153.72	VA
47	10.6	4.452	3.498	8.692	9.116	890.03	111.62	WA
48	23.8	8.092	6.664	23.086	20.706	992.61	152.56	WV
49	13.8	4.968	4.554	5.382	11.592	670.31	106.62	WI
50	17.4	7.308	5.568	14.094	15.660	791.14	122.04	WY
4								•

car crashes

Accidents in the states of the USA are examined. This is the data set of the cause of the accidents and the cost to the accident insurance companies.

- total -> Number of drivers involved in fatal collisions per billion miles
 (5.900-23.900)
- speeding -> Percentage Of Drivers Involved In Fatal Collisions Who Were Speeding (1.792-9.450)
- alcohol -> Percentage Of Drivers Involved In Fatal Collisions Who Were Alcohol-Impaired (1.593-10.038)
- not_distracted -> Percentage Of Drivers Involved In Fatal Collisions Who Were Not Distracted (1.760-23.661)
- no_previous -> Percentage Of Drivers Involved In Fatal Collisions Who Had Not Been Involved In Any Previous Accidents (5.900-21.280)
- ins_premium -> Car Insurance Premiums (641.960-1301.520)
- ins_losses -> Losses incurred by insurance companies for collisions per insured driver (82.75-194.780)
- abbrev -> USA states

In [11]: df.isnull().any()

Out[11]:	total speeding alcohol not_distracted no_previous ins_premium ins_losses	False False False False False
	ins_premium ins losses	False
	abbrev	False
	dtype: bool	

```
In [12]:

    df.isnull().sum()

    Out[12]: total
                                 0
              speeding
                                 0
              alcohol
                                 0
              not_distracted
                                 0
              no_previous
                                 0
              ins_premium
                                 0
              ins_losses
                                 0
              abbrev
              dtype: int64
In [13]:

    df.isna().sum()

    Out[13]: total
                                 0
                                 0
              speeding
              alcohol
                                 0
              not_distracted
                                 0
              no_previous
                                 0
              ins_premium
                                 0
              ins losses
                                 0
                                 0
              abbrev
              dtype: int64
 In [ ]:
In [14]:
              corr=df.corr()
              corr
```

C:\Users\TUPAKULA VAISHNAVI\AppData\Local\Temp\ipykernel_95376\318214091 0.py:1: FutureWarning: The default value of numeric_only in DataFrame.co rr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric_only to silence this warning.

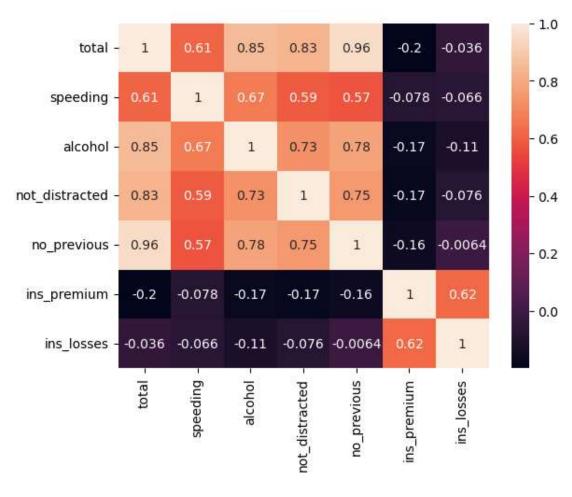
corr=df.corr()

Out[14]:

	total	speeding	alcohol	not_distracted	no_previous	ins_premium	i
total	1.000000	0.611548	0.852613	0.827560	0.956179	-0.199702	
speeding	0.611548	1.000000	0.669719	0.588010	0.571976	-0.077675	
alcohol	0.852613	0.669719	1.000000	0.732816	0.783520	-0.170612	
not_distracted	0.827560	0.588010	0.732816	1.000000	0.747307	-0.174856	
no_previous	0.956179	0.571976	0.783520	0.747307	1.000000	-0.156895	
ins_premium	-0.199702	-0.077675	-0.170612	-0.174856	-0.156895	1.000000	
ins_losses	-0.036011	-0.065928	-0.112547	-0.075970	-0.006359	0.623116	
4							

In [15]: ▶ sns.heatmap(corr,annot=True)

Out[15]: <Axes: >

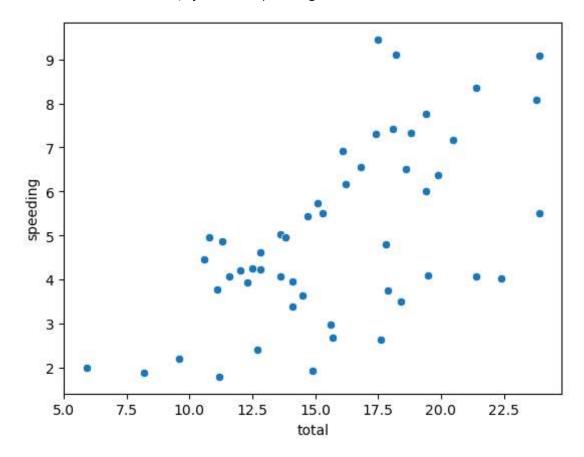


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Scatterplot

In [16]: N sns.scatterplot(x='total',y='speeding',data=df)

Out[16]: <Axes: xlabel='total', ylabel='speeding'>



Inference : From the graph it is evident that the total Number of drivers involved

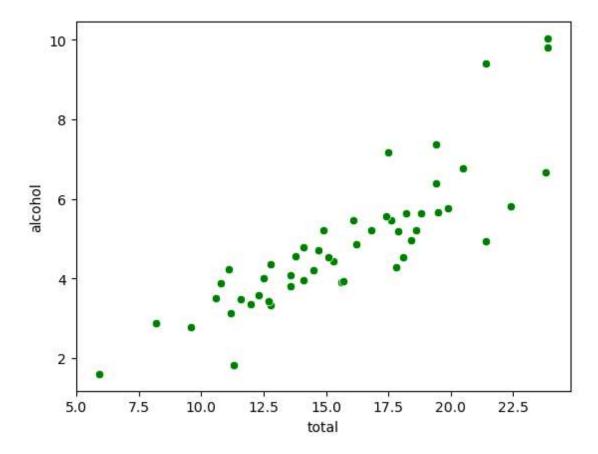
in fatal collisions is linearly proportional Percentage Of

Drivers

Involved In Fatal Collisions, Who were speeding.

In [18]: ▶ sns.scatterplot(x='total',y='alcohol',data=df,color="g")

Out[18]: <Axes: xlabel='total', ylabel='alcohol'>



Inference : From the graph it is evident that the total Number of drivers involved

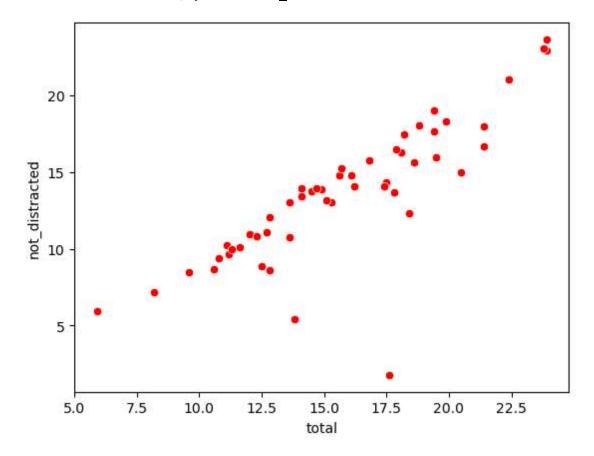
in fatal collisions is linearly proportional Percentage Of

Drivers

Involved In Fatal Collisions, consuming alcohol.

In [20]: N sns.scatterplot(x='total',y='not_distracted',data=df,color='r')

Out[20]: <Axes: xlabel='total', ylabel='not_distracted'>



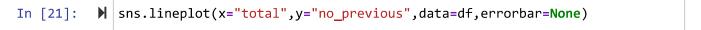
Inference : From the graph it is evident that the total Number of drivers involved

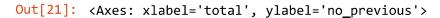
in fatal collisions is linearly proportional Percentage Of

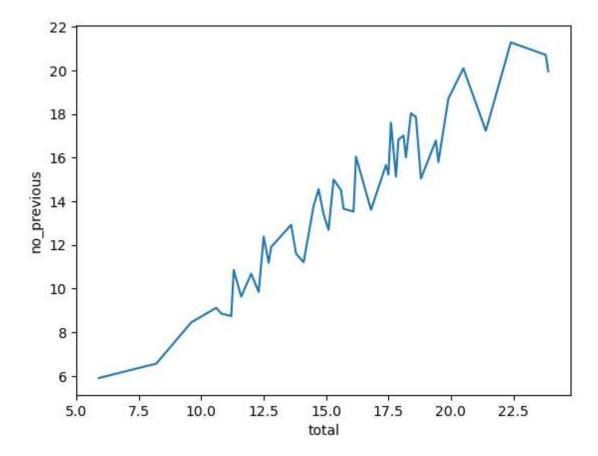
Drivers

Involved In Fatal Collisions Who Were Not Distracted.

Line Plot







Inference : From the graph it is evident that the total Number of drivers involved

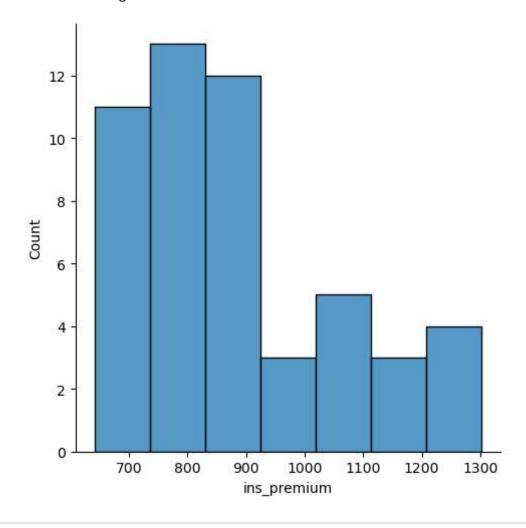
in fatal collisions is linearly proportional Percentage Of Drivers

Involved In Fatal Collisions Who do not have previous accidents.

Distribution plot

In [22]: N sns.displot(df['ins_premium'])

Out[22]: <seaborn.axisgrid.FacetGrid at 0x1e55caf4710>

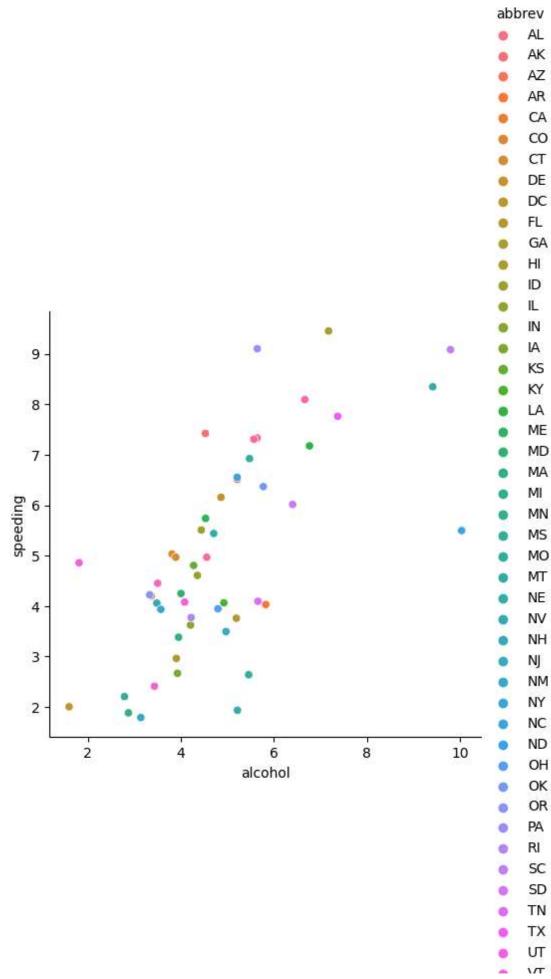


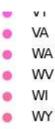
Inference : ins_premium mostly lies between 300 to 900

RelPlot

```
In [23]: In sns.relplot(x='alcohol',y='speeding',data=df,hue="abbrev")
```

Out[23]: <seaborn.axisgrid.FacetGrid at 0x1e55cb98c10>

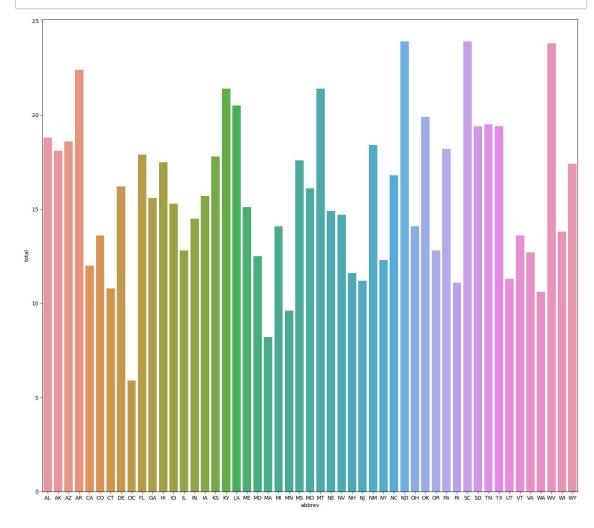




Inference: With an increase in alcohol consumption, speeding also increases

BarPlot

```
In [27]:  plt.figure(figsize=(18, 16))
    sns.barplot(data=df,x="abbrev",y="total")
    plt.show()
```

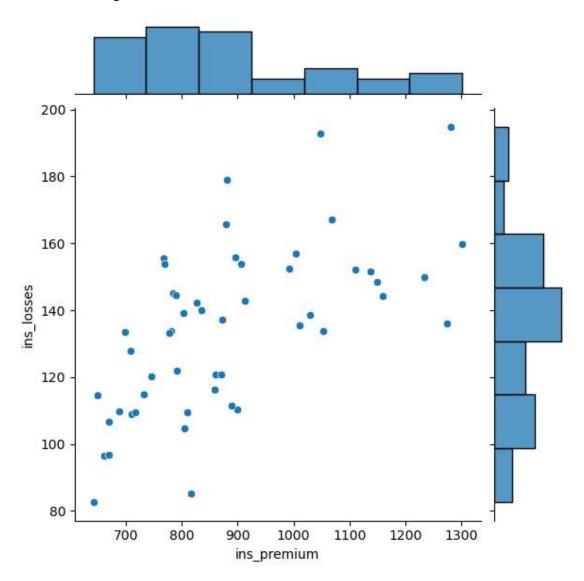


Inference : State ND has the total no.of highest collisions

JointPlot

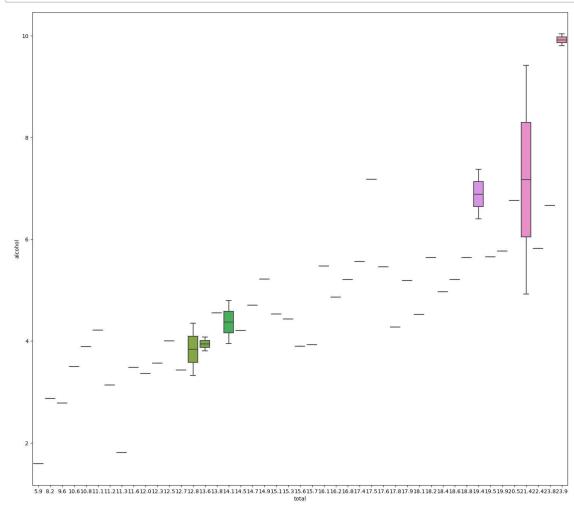
In [29]: N sns.jointplot(x="ins_premium",y="ins_losses",data=df)

Out[29]: <seaborn.axisgrid.JointGrid at 0x1e55cb6b510>



Inference : Premium and losses are directly related

BoxPlot



Inference : There are no outliers

In []: ▶